Making Project Selection Decisions: A Multi-Period Capital Budgeting Problem *

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2002

Abstract

Project selection is a major problem in managerial decision making. In this study, a deterministic model that schedules project starts is formulated as a binary integer program. This model is applicable in various settings such as selection of engineering projects in corporate planning, or in other planning environments in which the candidate projects are interdependent. The results of experimental runs with representative data show that the binary integer model can provide the required solutions in a very reasonable amount of time.

*Published in *International Journal of Industrial Engineering, 9(3) (2002) 301-310.*

Significance: Effective decision making is vital for any enterprise in coping with the rapid technological, social, and economical changes. Scientific decision making tools are essential for effective decision making. However, in many enterprises these tools are still not in extensive use and the decisions are generally made based on judgment and intuition. This managerial shortcoming results in an inadequate decision making process, thus reducing the competitiveness of these enterprises. A pivotal tool in scientific decision making is mathematical models. In this study, a project selection problem of a large enterprise is formulated as a mathematical program. Promising results of the analysis and the computational experiments indicate that this approach can provide effective decision support in practice.

Keywords : Decision Making; Project Selection; Decision Support Systems; Planning, Programming, and Budgeting Systems (PPBS); Binary Integer Programming; Capital Budgeting; Knapsack Problems.

1 Introduction

Effective decision making is vital for any enterprise in coping with the rapid technological, social, and economical changes. Scientific decision making tools are essential for effective decision making. However, in many enterprises these tools are still not in extensive use and the decisions are generally made based on judgment and intuition. This managerial shortcoming results in an inadequate decision making process, thus reducing the competitiveness of these enterprises. A pivotal tool in scientific decision making is mathematical models. Mathematical models process data and transform them into relevant information. The role of models in decision making is aptly expressed by Bisschop and Meeraus [7]:

> "[Models] are used as a framework for analysis, for data collection, and for discussion. They are created to improve one's conceptual understanding of the problem. If several decision makers and/or institutions are involved in a final decision or set of recommendations, models can be used as neutral moderators to guide the discussions. Different viewpoints can be tested and examined. In such an environment the actual values resulting from testing different scenarios are of interest. The model is a learning device, and should never be expected to produce final decisions."

Project selection is a major problem in managerial decision making. For instance, it is central to the portfolio selection process in investment planning and evaluation of engineering projects in engineering economic analysis. Essentially it is a resource allocation problem: determining the distribution of limited budgetary resources among competing alternative projects. Because effective and efficient management of scarce resources is of paramount importance in every organization, this area has received considerable attention in the literature (see Section 3).

In this study, a deterministic model that schedules *project starts* is formulated as a binary integer program. It is argued that the best way to utilize this model is in the context of a decision support system. Since such project selection problems usually have long planning horizons and far-reaching strategic impacts on the enterprise, the decision makers should use judgment and insight in addition to the scientific decision making tools. Furthermore, the results obtained must be analyzed by the decision makers based on their experiences of similar situations in the past and their intuition about the future.

The paper is organized as follows. In the next section, the characteristics of the system studied are summarized. The problem discussed in this paper originated from a study done for the *Ten-year Acquisition Program*, OYTEP[1] of the Turkish Armed Forces. As it is emphasized in that section, the fact that the projects in question are defense related military projects is immaterial to the model developed and the approach suggested in the remainder of the paper. The model formulated in Section 3 is equivalently applicable in various settings, such as, engineering project selection in corporate planning, or multi-period portfolio selection in investment analysis, or in any other planning environment in which the candidate projects are interdependent. In Section 4, the computational validation of the model is presented. Since the model will be an integral part of a decision support system and will need to be run a number of times for various scenarios, it should be able to produce very fast solutions for problems with realistic input data size and structure. Section 5 presents a brief overview of decision support systems and suggestions for how to incorporate analytical models in the context of such systems. The paper concludes with a summary of the results obtained.

2 Characteristics of the System

The Turkish Armed Forces uses the *Planning, Programming, and Budgeting System* (PPBS)[2] as its primary decision making process for managing its resource allocation activities. The OYTEP problem, which was the main concern of this study, is a part of this PPBS process.

Planning, Programming, and Budgeting System PPBS is essentially a systematic process for allocating defense resources. The purpose of the PPBS is to provide the best mix of troops, equipment, and logistic support within the limitation of fiscal constraints. It establishes a framework and provides a process for decision making for the future, as well as, an opportunity to reexamine prior decisions in the light of the present environment (e.g. evolving threat, changing economic conditions, etc.) PPBS is a cyclic

[1] OYTEP is the Turkish acronym for *Ten-Year Acquisition Program*: *On Yıllık Tedarik Programı*.

[2] A tutorial [2] on PPBS is available on the Web.

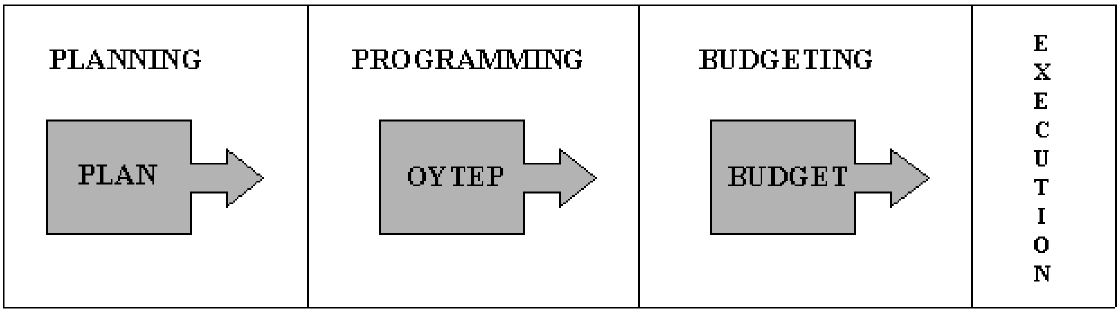

Figure 1: The PPBS process

and iterative process consisting of three distinct but interrelated and overlapping phases. The PPBS phases and the output of each phase are shown in Figure 1.

The PPBS Process

Planning This is the first step in the process. During this phase, the objectives are to identify threats to national security, to determine current capabilities to meet those threats, and to recommend forces and systems necessary to overcome them. The output of the planning phase is the *Strategic Goal Plan*.

Programming The purpose of this phase is to translate the output of the planning phase into a ten-year resource proposal. In order to accomplish this, information on the available funding is needed, in addition to the *Strategic Goal Plan*. The challenge in this phase is to effectively apply a fiscal constraint to non-fiscal output of the planning phase. An acceptable proposal which assigns the available money to projects in a most effective way should be formulated. The output of this phase is the *Ten-year Acquisition Program (*OYTEP*)* document. The decisions made in this phase form the basis for the next phase: budgeting.

Budgeting The budgeting phase of PPBS reviews the first two years of OYTEP. The purpose is to develop an executable proposal that will best accomplish the approved programs of the Armed Forces. It is important to note that the major objective here is not to revise the priorities and programs that were developed in the planning and programming phase. But rather, it is to form a budget that will most efficiently execute those priorities and programs. The emphasis in this phase is more on execution and less on program utility. The key difference between programming and budgeting is the level of precision and accuracy associated with resource estimates. More precise budget estimates are required to make certain that the budget is executable. The budgeting phase provides the decision maker a final opportunity to reexamine the estimates to reflect the most accurate and up-to-date data available.

The Problem The OYTEP document is a product of the programming phase of the PPBS cycle. This document identifies the allocation of the resources to the projects which are evaluated in a ten-year horizon to achieve the requirements determined in the *Strategic Goal Plan*. In the *Strategic Goal Plan*, the aim is to create the planned force structure by accomplishing the projects that will eliminate capability deficiencies. Reasonably accurate forecasts of the procurement budgets allocated for OYTEP use for the next ten years are easily obtainable. During this time all the projects in the *Strategic Goal Plan* are evaluated, and then the OYTEP document is formulated under the budget constraints and is updated biennially.

The OYTEP decision makers must achieve the best overall "*defense contribution*" by selecting the projects and deciding their start times over a ten-year planning horizon, subject to fiscal constraints and other side conditions. It is not straight forward to estimate the "defense contribution" of a project. Özkil and Gürsoy [25] proposed a model to determine the defense contributions of projects with maximal consensus among the involved parties, such as the Army, the Navy, and the Air Force. Fiscal constraints of this problem are the yearly procurement budgets estimated over a ten-year planning horizon. Since these parameters are based on estimates, they can be highly subjective. Furthermore they are soft, in the sense that minor violations of these constraints, though not desirable, are permissible.

Not all projects involved in this analysis are independent. In this study, two main types of interdependencies among the candidate projects are considered:

Disjunctive projects: A set of projects may have the same objective, and therefore, at most one can be selected.

Dependent projects: It is possible for a major, primary project to have a number of secondary, *dependent* projects. The *dependent* projects can be selected only if the major, *primary*, project is selected. Furthermore, there may be a certain level of timing dependency between the primary and the dependent projects. For example, a dependent project can start at the earliest so many years prior to (or after) the start of the primary project. There may also be similar restrictions on the completion of the projects.

3 The Model

Assume there are N *projects* to schedule. If project j ($j = 1, \ldots, N$) is selected, it can start at any year k ($k = 1, \ldots, T$) and continue for the *duration*, d_j, without preemption. Formally, the planning horizon is T. In order to allow any project j to start at period T, at the latest, and be completed at the end of period $T + d_j$, the planning horizon is taken as $T' = T + (D - 1)$, where

$$D = \max_j \{d_j\}.$$

The associated indicator variable is defined as:

$$x_{jk} = \begin{cases} 1, & \text{if project } j \text{ starts at year } k = 1, \ldots, T', \\ 0, & \text{otherwise.} \end{cases}$$

Let β_{jl} be the resource requirement of project j during the year l ($l = 1, \ldots, d_j$) of its inception, and define

$$b_{jkt} = \begin{cases} 0, & \text{if } t < k, \\ \beta_{j(t-k+1)}, & \text{if } k \leq t < k + d_j, \\ 0, & \text{if } t \geq k + d_j. \end{cases}$$

Then b_{jkt} is the resource requirement of project j during year t if it is started in year k. Let B_t denote the total amount of resource available in year t ($t = 1, \ldots, T'$).

Let γ_{jl} be the return of project j during the year l ($l = 1, \ldots, d_j$) of its inception, and define

$$a_{jkt} = \begin{cases} 0, & \text{if } t < k, \\ \gamma_{j(t-k+1)}, & \text{if } k \leq t < k + d_j, \\ 0, & \text{if } t \geq k + d_j. \end{cases}$$

Then a_{jkt} is the return of project j during year t if it is started in year k.

Let S denote an ordered set of pairs $(i, j) \in [1, \ldots, N] \times [1, \ldots, N]$ where $i \neq j$. Define $q_{ij} > 0$, as the maximum allowable time lag for project j to start before project i is started, and define $q_{ij} < 0$, as the minimum allowable time lag for project j to start after project i is started. Similarly, $r_{ij} > 0$ is defined as the maximum allowable time lag for project j to be completed after project i is completed and let $r_{ij} < 0$ denote the minimum allowable time lag for project j to be completed before project i is completed (see

Figure 2). Note that the following strict inequality must hold for all pairs $(i, j) \in S$,

$$q_{ij} + d_i + r_{ij} > d_j.$$

If $q_{ij} + d_i + r_{ij} = d_j$, then the start and the completion time for project i is fixed with respect to project j, and therefore the projects i and j can be treated as a single project. Clearly, if $q_{ij} + d_i + r_{ij} < d_j$, then there is no feasible way to schedule project i with respect to project j. Finally, for project i to be able to start in year k ($k = 1, \ldots, T$), project j must have started at the earliest,

$$\nu(i, j, k) = \min\{\max\{1, k - q_{ij}\}, T'\}, \tag{1}$$

and at the latest,

$$\mu(i, j, k) = \min\{\max\{1, k + d_i + r_{ij} - d_j\}, T'\}. \tag{2}$$

Let G_h denote the sets of mutually exclusive, disjunctive projects ($h = 1, \ldots, H$). At most one project can be selected from each set.

It is usually customary to maximize the total *discounted* returns. Letting α be the discount factor and defining net present worth of project j as,

$$p_{jk} = \sum_{t=1}^{T} (1 + \alpha)^{-(t-1)} a_{jkt}, \quad j = 1, \ldots, N \text{ and } k = 1, \ldots, T,$$

the problem can be stated as

$$\max \sum_{j=1}^{N} \sum_{k=1}^{T} p_{jk}\, x_{jk}$$

subject to:

$$\sum_{k=1}^{T'} x_{jk} \leq 1, \quad j = 1, \ldots, N \tag{3}$$

$$\sum_{j=1}^{N} \sum_{k=1}^{T'} b_{jkt} x_{jk} \leq B_t, \quad t = 1, \ldots, T' \tag{4}$$

$$\sum_{k=1}^{T} x_{ik} = \sum_{k=1}^{T'} x_{jk}, \quad \text{for all pairs } (i, j) \in S \tag{5}$$

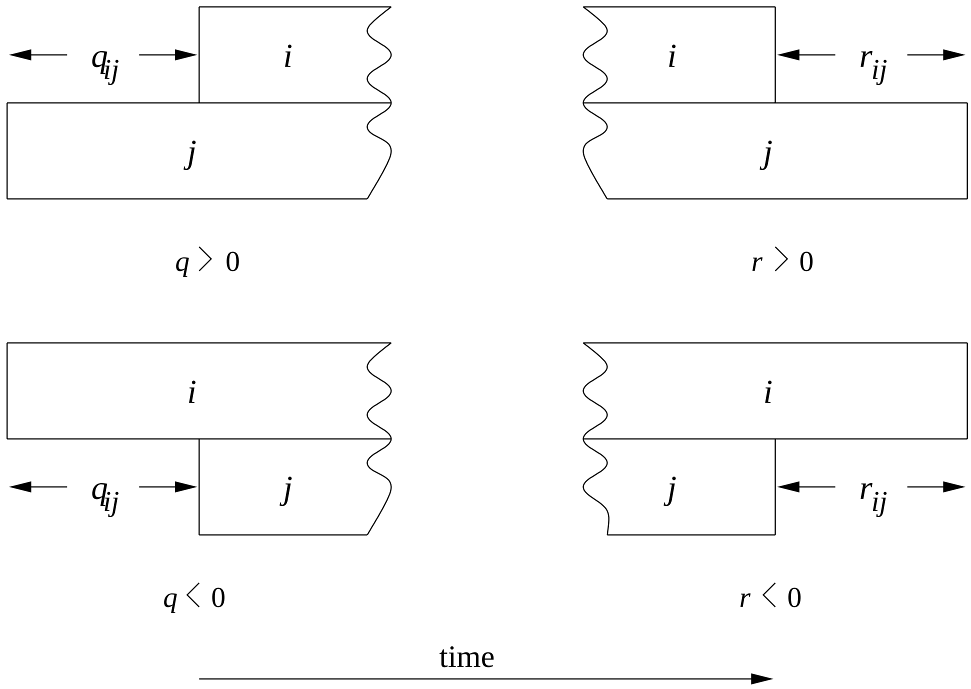

Figure 2: Alternative start and completion times for a pair of projects (i, j)

$$x_{ik} \leq \sum_{m=\nu(i,j,k)}^{\mu(i,j,k)} x_{jm}, \quad k = 1, \ldots, T, \tag{6}$$

$$\text{for all pairs } (i, j) \in S,$$

$$\sum_{j \in G_h} \sum_{k=1}^{T} x_{jk} \leq 1, \quad h = 1, \ldots, H \tag{7}$$

$$x_{jk} \in \{0, 1\}, \quad j = 1, \ldots, N \text{ and } k = 1, \ldots, T'. \tag{8}$$

Constraint (3) ensures that any project can start only once. Constraint (4) states that the total resource requirement of the selected projects must be less than or equal to the total amount of resource available for that year. Constraint (5) ensures that, for all pairs $(i, j) \in S$, if project i is chosen then project j must also be chosen, and vice versa. Relaxing this constraint, allows the possibility for choosing project j without necessarily choosing project i. Constraint (6) enforces the feasible start times of projects i and j with respect to each other, where $\nu(i, j, k)$ and $\mu(i, j, k)$ are defined in (1) and (2), respectively. Finally, constraint (7) ensures the selection of only one project in each group G_h ($h = 1, \ldots, H$).

Previous Work The formulation given in the previous section is basically a multi-period capital budgeting problem with side conditions. The capital budgeting problem determines which projects to fund given a constraint on available capital. The net present value (NPV) of each project is calculated. and the objective is to maximize the NPV of the sum of the chosen projects subject to funding constraints.

The capital budgeting problem is one of the first integer programming problems studied. It was first posed by J. H. Lorie and L. J. Savage [20] as:

$$\max \sum_{j=1}^{n} c_j \, x_j$$

subject to:

$$\begin{aligned} \sum_{j=1}^{n} a_j \, x_j &\leq b \\ x_j &\in \{0, 1\}, \; j = 1, \ldots, n. \end{aligned}$$

where n *projects* are under consideration, and c_j is the *net present value* of project j, and a_j is the *capital* required to fund project j. The *total capital available* for all projects is b. The decision variable, x_j, is equal to 1 if project j is funded and 0 if not.

Weingartner [34] analyzed the above "Lorie-Savage Problem" and established a framework for the capital budgeting problems. Following his pioneering work, an extensive literature was developed on the mathematical approaches to capital budgeting problems using linear programming [5], [35], [11], [24], [26]; goal programming [14]; nonlinear programming [26]; mixed-integer programming [8], [16]; and simulation [17], [29], [19].

Bean et al. [4] solved a multi-period version of the problem where the objective is to maximize net cash present value profit by divesting assets subject to certain lower bounds on the return on equity that companies must achieve each year. Another integer programming formulation was given by Hall et al. [12]. The problem is to decide on project funding at the National Cancer Institute of U.S.A. The fleet mix planning of the U.S. Coast Guard is discussed as a capital budgeting problem by Bhargava [6]. In this paper, the problem is to determine a set of new assets that can be obtained using a given capital so as to maximize the performance of the fleet. For a review of approaches to the capital budgeting problem, including parametric, chance-constrained, and quadratic programming formulations see Levary and Seitz [18].

The capital budgeting problem is also referred to as the multidimensional knapsack problem in the literature [23]. The knapsack problem [10] is NP-hard in the ordinary sense [27]. The time requirement for the optimal solution grows exponentially with the size of the instance. In addition to the exact methods based on the branch and bound approach, there are numerous heuristic methods proposed for this problem. These heuristics may obtain good solutions that are close to optimal, in general, but do not guarantee optimality. Good heuristic methods that yield approximate solutions to multidimensional knapsack problems are proposed by Senju and Toyoda [30], Toyoda [32], Balas and Martin [3], Hillier [13], Kochenberger et al. [15], and Magazine and Oğuz [21]. A comprehensive review of knapsack problems is given by Pisinger and Toth [28].

4 Computational Experience

The OYTEP problem, which motivated this study, is comprised of approximately 1,000 projects. The mathematical programming formulation of the problem requires approximately 10,000 binary variables and 2,500 constraints. A series of computational experiments were conducted and near-optimal solutions were obtained with very reasonable solution times. Since the actual data for this problem is classified, randomly generated data sets having the same general "density" and the same relative magnitudes as the real problem were used.

Test Problems A total of 10 random problems were generated varying in size from 908 projects to 1,067 projects. Their parameter values were chosen as follows

- the number of projects drawn were from the uniform distribution [900, 1100],
- the return of projects drawn were from the uniform distribution [1, 100],
- the resource requirement for projects drawn were from the uniform distribution [1, 1000],
- the duration of projects were determined using normally distributed random numbers with a mean 7 and variance 2,
- the budget values for each year were determined in a way that the number of chosen projects were roughly one fourth of the total number of projects,
- the dependency conditions were defined for 30 of the projects in each test problem.

Computational Results The initial trial runs were made using the GAMS [9] model[3] of the problem with CPLEX 4.0.7 software. For the actual runs, the formulation was modeled using the modelling language OPL[4] [1] and the ran-

[3]The GAMS code and solutions can be found at (http://www.ie.bilkent.edu.tr/archive/research/serdar-yavuz/gams/).

[4]The OPL code and solutions of representative test problems are available at (http://www.ie.bilkent.edu.tr/archive/research/serdar-yavuz/opl/).

Test Problem	J	N	M	C	t	%
1	908	9,080	2,144	213	121.33	98.54
2	1,009	10,090	2,368	250	151.01	98.83
3	942	9,420	2,234	249	125.64	98.82
4	1,064	10,640	2,478	226	156.38	98.78
5	996	9,960	2,342	227	145.71	98.41
6	958	9,580	2,266	222	149.98	98.86
7	935	9,350	2,220	241	141.49	98.77
8	1,067	10,670	2,484	225	154.22	98.48
9	918	9,180	2,186	232	125.63	98.03
10	973	9,730	2,296	231	131.21	98.99

Table 1: Test problems and their solution time, t.

domly generated representative problems were solved with CPLEX 6.5.3 on SunOS 5.5-SPARCserver 1000E.

The results of the computations are shown in Table 1. The column headers are given by

J - number of projects,

N - number of variables,

M - number of constraints,

C - number of selected projects.

t - solution time in seconds,

% - objective value of the solution found as a percentage of the objective value of the LP relaxation,

The average solution time is 140.26 seconds with a maximum of 1.97 % decline from the objective value of LP relaxation. Both of these two figures are very encouraging. Computational times under three minutes are much better than expected. It is interesting to note that the maximum run time was less than three minutes, and that the variance of the resulting values of t (and that of %) is very low. This implies that the problem with actual data can be run well under five minutes. If the decision makers need to make last minute changes, then the problem can be remodeled, run, and the new solution can be obtained within a few minutes.

Obtaining integer feasible solutions within 2% of the optimal LP relaxation is very satisfactory. Usually the objective function coefficients, i.e. the *project returns*, are subjective estimates, and thus it would be superfluous to insist on a tighter stopping rule. This is particularly true when the decision makers, in order to ascertain the sensitivity of parameter values, want to perform multiple runs with different estimates for project returns. Hence these run times obtained indicate viable implementation of such tools in practice.

5 OYTEP Decision Support System

The results of the experimental runs with representative data show that the binary integer model developed in Section 3 can indeed provide the required solutions in a very reasonable amount of time. Project selection problems of this magnitude have long-term strategic impacts, and it is often difficult to predict the possible future effects of these decisions. For these reasons, post-optimality analysis requiring numerous runs is of utmost importance. All these features indicate the necessity of designing a decision support system (DSS) for this problem. The characteristics of a DSS envisioned for project selection problems of the type discussed in this paper is succinctly stated by Makowski [22]:

- A DSS is a supportive tool for the management and the processing of large amounts of information and logical relations that help a decision maker to extend his habitual domain, thus help him to reach a better decision. In other words, a DSS can be considered as a tool that, under full control of a decision maker, performs the cumbersome task of data processing and provides relevant information that enables a decision maker to concentrate on this part of the decision making process that cannot be formalized.

- A DSS is a problem dedicated system designed for a specific decision making process and its environment. The functioning of a DSS should be consistent with the actual environment of a decision making process. A DSS is often tuned for a specific decision maker.

- A DSS is not a *black box type* tool. The structure and functioning of a DSS (including explicit and implicit consequences of assumptions adopted for its design) must be such that a decision maker understands and accepts them. The user interface of a DSS is designed in such a way that a decision maker may obtain, from the DSS, information and answers of questions that he considers to be important for a decision making process.

- A DSS is not intended to solve a decision problem. Therefore it should not support reaching a single or unique decision nor should it restrict a possible range of decisions.

- A DSS should support a user during a decision making process by providing two main functions. First, it allows for examination of consequences of any (feasible) decision. Second, it helps in finding decisions that are best for attaining goals specified by a user.

These decision support systems are basically interactive computer-based information systems that help the decision makers utilize data and models to solve unstructured problems [31]. They consist of three main components: model base, a database, and an interactive software system for linking the user to each of these. A conceptual view of the OYTEP DSS is illustrated in Figure 3. It is beyond the scope of this paper to discuss the details of the required database and user/system interface. As to the model base, it should include, in addition to the binary integer programming model presented and analyzed in the previous sections, the multi-criteria consensus model of Özkil and Gürsoy [25] that was briefly outlined in Section 2.

The model developed in Section 3 is basically a multi-period capital budgeting model with side conditions. It is essential that the decision makers understand and accept the structure and the functioning of this model. To this end and to illustrate the benefits of such models, a simplified spreadsheet model[5] of the problem has been found to be most beneficial; this model contains both data and the solution cells. An example of a model is shown in Figure 4. This model has data windows for projects, namely resource requirements of projects, and *defense contribution* of projects and the total amount of resource available at each year. As a template, the user can provide these windows with different values and make changes to analyze various situations. Selected projects and their start years are also shown in

[5]The template and the demo spreadsheets for OYTEP problem are available at: (http://www.ie.bilkent.edu.tr/archive/research/serdar-yavuz/spreadsheets/)

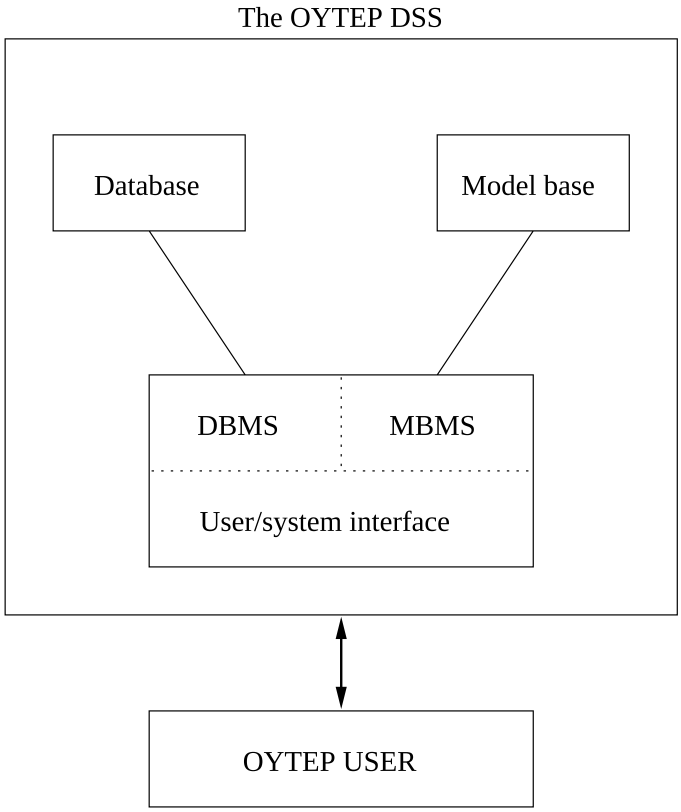

Figure 3: The components of the OYTEP DSS

the decision window. After the model is run, information on the yearly budget and return is provided. After obtaining this information, the user can make slight changes in each year's available budget and then see the results in related cells. Finally the total return is displayed at the right-bottom cell.

6 Conclusions

The problem investigated in this study is selection of interdependent projects over a ten-year planning horizon in order to satisfy the strategic goals of an enterprise. The binary programming model developed is essentially a multi-period capital budgeting problem with side conditions. Experimental runs with representative data resulted in very promising computational times, suggesting that the problems with actual data can be run well under five

OYTEP MODEL

Resource requirement of projects

Budget	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Project 1	10	12	18	20	20	22	22	22	0	0
Project 2	6	12	14	16	16	16	18	18	18	0
Project 3	14	16	20	20	20	0	0	0	0	0
Project 4	8	12	16	16	20	20	0	0	0	0
Project 5	34	34	34	0	0	0	0	0	0	0

Defence contribution of projects

Return	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Project 1	1	1	5	10	10	10	10	15	0	0
Project 2	2	8	8	8	8	8	8	8	8	0
Project 3	4	10	15	15	15	0	0	0	0	0
Project 4	2	2	10	10	10	10	0	0	0	0
Project 5	8	35	35	0	0	0	0	0	0	0

Total amount of resource available

TOTAL	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Budget	67	68	65	72	73	67	65	69	75	76

Decision	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	
Start Project 1 at	-6,7E-12	0	0	1	0	0	0	0	0	0	1
Start Project 2 at	0	1	0	0	0	0	0	0	0	0	1
Start Project 3 at	0	1	0	0	0	0	0	0	0	0	1
Start Project 4 at	-6,7E-12	0	0	0	1	0	0	0	0	0	1
Start Project 5 at	1	-6,7E-12	0	0	0	0	0	0	0	0	1

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Budget used at	34	54	62	44	56	66	52	54	60	60

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	**TOTAL**
Return at	8	41	53	24	26	30	28	28	28	28	294

Figure 4: The spreadsheet model

minutes. This is especially important because post-optimality analysis is an indispensable part of the solution process. Moreover, it is imperative that the whole process be integrated in the framework of a decision support system [33]. Such a computer-based information system that combines analytical decision models and data with extensive user involvement is a must in the analysis of strategic problems of the type discussed in this paper.

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